EARLY DETECTION OF DIABETIC RETINOPATHY IN RETINAL IMAGES USING THE PROPOSED CONVOLUTIONAL NEURAL NETWORKS

A SYNOPSIS

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1. INTRODUCTION

Between 2000 and 2030, 171 million people worldwide will have diabetes. This will increase to 366 million. Diabetic Retinopathy (DR) can cause retinal damage such as Micro neuropathy, severe and mild exudates, and macular edema. Automated analysis of retina imaging is important for the diagnosis of retinal diseases, especially glaucoma and DR [1]. The vascular tree of the retina is a complex structure of arteries and veins that often interconnect and diverge in all joints of the eye. The analysis of this structure plays significant role in the diagnosis and monitoring of many diseases. The retina is the single structure of the human body where the vascular system can be studied in vivo and without invasive measures [2]. Extensive analysis of retinal blood vessels should identify the horizontal and vertical vessels of the vessel, which may indicate signs of vascular dysfunction or degeneration [3]. Significant clinical use is important for the localization and identification of this identity. For example, fracture analysis offers measures such as fracture angles studied as biomarkers of blood pressure and other heart diseases. Methods for analyzing clinical conditions related to retinal indicators, including procedures for Content-Based Image Retrieval (CBIR) programs, use aspect and perspective vectors related to the unique descriptive properties of images stored in the CBIR database [4]. Identifies at least one properly protected image from the archive based on the similarity of its components or structures. Many factors contribute to the development of diabetes, including physical activity, obesity, inactivity, and lack of awareness [5]. However, diabetes is associated with microbial problems such as nephropathy, neurosis, and retinopathy. The most common problem in diabetic patients is DR, which is often not diagnosed until the dangerous stage of advanced vision has passed.

Early detection and prevention of DR is needed to reduce the incidence and progression of blindness. A multidisciplinary method comprising routine eye inspection and reversible risk factors, are effective in reducing vision loss by 98%. DR is a major complication of diabetes that is now referred to as a vital reason for blindness. DR is a serious eye disease caused by high blood sugar, which causes damage to the blood vessels behind the retina and usually caused by inflammation and leakage. The fundus images were used for the detection of DR stages [6]. Color fundus imaging with automatic detection of bleeding in the presence of micro arthritis and design features marked as dynamic characteristics does not require accurate classification of the classified areas. Super-pixel Multi-Feature Classification (SMFC) [15] divides an image into a series of super pixels that are considered candidates. Next, the main features of these candidates and new features of the environment were proposed. The automatic

trauma detection program consists of four main stages: character extraction, visual disc removal, and pre- and post-operative trauma detection. The differential evolution method is used for the optimal value of the ambiguity function parameter that defines the boundaries of the candidate domain segment. Parallel structures [7] are used to classify recurrence of microaneurysms according to continuous retinal images and consistent pathological factors. Multiple Instance Learning (MIL) systems are used to avoid indirect information about video-level concepts. The MIL-based DR detection system uses integrated event encryption optimization and image classification scale. Color retinal imaging is divided into two types, and DR is automatically detected using computer-aided diagnostic technology that uses advanced learning techniques. Systems based on CNN structure used to detect and classify different levels of DR in color images.

2. LITERATURE SURVEY

Faura et al. [1] suggested the concept of using sensor arrays for diabetes screening, which involves the simultaneous detection of multiple analytes in a patient's biological sample. The paper further explores the use of colorimetric and electrochemical sensors in combination with sensor arrays to detect specific biomarkers associated with diabetes mellitus and diabetic retinopathy.

Gupta et al. [2] developed an optimized hybrid machine learning approach for diabetic retinopathy detection using smartphones. The approach combines multiple machine learning algorithms, such as convolutional neural networks (CNNs) and support vector machines (SVMs), to extract relevant features from retinal images and classify them into different stages of diabetic retinopathy.

Das and Saha [3] focuses on the optimization of the CNN using a genetic algorithm. The genetic algorithm is employed to automatically search and select the optimal hyper parameters and architecture of the CNN, improving its performance for diabetic retinopathy detection.

Lim et al. [4] explores various interpretability techniques that have been applied to deep learning models for diabetic retinopathy analysis. These techniques include gradient-based methods, such as gradient-weighted class activation mapping (Grad-CAM), occlusion sensitivity, and saliency maps, which highlight the regions of the image that contribute most to the model's decision and interpretability techniques discussed in the paper include layer-wise relevance propagation (LRP), guided backpropagation, and class activation mapping (CAM).

Masud et al. [5] in this work they discussed dataset used for training and testing the CNN model, which typically consists of a large number of labeled retinal images with different stages of diabetic retinopathy. They discuss the data preprocessing steps involved in standardizing the images, such as resizing, normalization, and augmentation, to enhance the robustness and generalizability of the CNN model.

Elsharkawy et al. [6] focuses on the development of a higher-order spatial appearance model using the 3D-OCT data. The authors explain that this model captures both local and global spatial characteristics of retinal features, enabling more comprehensive and accurate analysis for diabetic retinopathy detection. They describe the process of constructing the model, which involves extracting relevant features from the 3D-OCT images and incorporating them into a statistical model.

Luo et al. [7] proposed MVDRNet, which consists of multiple DCNNs and attention mechanisms. Each DCNN is designed to extract features from a specific view of the retinal images. The extracted features are then fused using attention mechanisms, which prioritize relevant information and suppress irrelevant or noisy features and discuss the training process of MVDRNet, including the selection and preparation of the dataset for diabetic retinopathy detection

Cai et al. [8] suggested a label-efficient Convolutional Neural Networks (CNN) architecture (ADLCNN) is one of the most active learning methods known as predicted gradient length. The ADLCNN system selects the most informative links and images and uses the original sample text labels to understand the complexity of retailing from the simplest. This is an effective prognostic mask to assist physicians in critical areas of retinal angiography, from the description of critical eye samples to five level-DR. The average SE of the ADL-CNN model is 92.20%, SP 95.10%, F level 93%, and ACC 98%.

Amarapur [9] Classification algorithms based on the Deep Belief Network (DBN) typically classify images into four categories. Optimal performance is selected based on an improved gear and steering mechanism using an improved metal mechanism called the modified gear and steering-based rider optimization algorithm (MGS-ROA) The same algorithm increases the weight of the DBN. This model shows consistent and reliable performance with efficient performance and benchmarks compared to existing models. Experimental results show that the methods developed for DR detection work well at all levels.

These include image processing techniques such as angiogenesis detection, resizing, green channel filtration, gas filtration, erosion and enlargement.

Abualigah et al. [10] The CNN classifier has been integrated with the VGG-16.NET and has tested over 2,200 images from the Kaggle database. The sensitivity, specifications and accuracy of the actuator database are 0.802, 0.974 and 0.959, respectively, and the sensitivity, specifications and accuracy of STARE are 0.801, 0.969 and 0.961, respectively.

Desai and Shah [11] they proposed for detailed studies of DR detection from image processing and retinal bed imaging. Images of the retinal region are highlighted using a practical approach that includes Histogram Equalization (HE) and Contrast Local Adaptive Histogram Equalization (CLAHE). HE and CLAHE are well-known image enhancement solutions that can be easily matched with the image data of the target.they classified using CNN and evaluated system performance using the MESSIDOR database of 400 website images.

Masadeh et al. [12] developed models based on CNN and trained them over publicly available databases. This model performed better than previous studies in similar public databases. As a result, CNN has important functions to perform tasks such as automatic diagnostics on digital medical films. Using the Macedor-2 reference test database, the model received 0.92 AUC estimates with 81.02% and 86.09% sensitivity, respectively. The sensitivity and specificity of AUC Messidor-1 are 0.958, 88.84% and 89.92%, respectively.

Qureshi et al. [13] focuses on using machine learning to find effective ways to diagnose highly effective illnesses. This disease can be detected early using machine learning. Early diagnosis cures the disease. If the disease is not detected early, it becomes more dangerous day by day and one loses permanent vision. Many machine learning techniques such as SVM, KNN, and CNN are useful for diagnosis. Analysis and discussion of results have shown that SVM is effective in diagnosing DR.

Bodapati et al. [14] The DR detection and classification algorithm is based on CNN. In this method, the film is first processed to separate the blood vessels. The entrance gate is separated by a very large linear curve with very high Hessian matrix characteristics. Adaptive histograms improve balance and morphological openings, making it possible to eliminate defects. CNN creates excitement and connectivity between two neural network subnets.

Math and Fatima [15] Descriptive classification is used to describe a DL classification model based on the distribution of scores obtained in the final pixel layer of the input image

being analyzed. A general theoretical derivative of a traditional DL design module for building distributed networks of all types of applications based on the DL model. The observed pixel distribution model for each neuron divides the observed output score into two components. Visual maps created this way can be easily explained by ophthalmologists, and basic statistical algorithms can help diagnose this eye disease.

Das et al. [16] The layout of the CNN is based on the transfer of color photos. Determining the DR class based on the minimum structure of a database of solid exudates, blood vessels, 3050 film and 419 test images is very useful. This model is very powerful and works well in small live applications that are lightweight and have limited computing power, speeding up the selection process. Using the preconfigured DenseNet, they found some very useful migration and development training in this database

3. RESEARCH PROBLEM

In Eye related diseases, DR and Glaucoma are the most two important diseases. Among them, DR is irreversible disease related with human retina. In present method, the DR images are scanned and screened by the expert ophthalmologist. The earlier screening of DR is important to prevent the vision loss in patients. Hence, the diabetic patients are periodically under goes for eye checking with expert ophthalmologist. In present method, the ophthalmologist screens the DR which consumes more time and hence it is not suitable for large population countries. This problem is overcome by proposing novel automated DR screening methodologies for the earlier detection of DR in this research work.

4. RESEARCH OBJECTIVES

The objectives of the research work are:

- To detect Diabetic Retinopathy in retinal images using Ensemble Classifier with Deep Learning Techniques.
- To propose recurrent neural network with long short-term memory (RNN-LSTM) is used to classify DR images as multiple disease class.
- A propose a convolutional neural network based sea lion optimization (CNN-SLO) algorithm.it can generalize well to unseen retinal images and datasets. CNN-SLO model should be able to accurately detect and classify diabetic retinopathy.

5. RESEARCH METHODOLOGY

5.1 Diabetic Retinopathy Prediction and Analysis Using Ensemble Classifier in Deep Learning Technique

We propose an Ensemble algorithm to predict diabetes from retinal images. The primary goal of this work is to enhance the accuracy and predict the result with minimum time consumption. The proposed system is a two-phase work in which, the initial bootstrap resampling method is employed for extracting the subsamples. Next, the classified decision tree establishes a voting system for finalizing the prediction result. The performance accuracy achieved by the proposed Ensemble algorithm is compared with the logistic regression and Deep Neural Network (DNB).

The proposed Ensemble model is an extension of the traditional random forest (RF) algorithm. Breiman first proposed it as a combination method in 2001. It results from the classification based on the random forest classification, random forest regression, and continuous value. Several research demonstrated that the outcomes of the random forest algorithm had superior accuracy predictions that eliminated noise and aberrant values. The proposed enhanced Ensemble classifier model is two-phase work that applies a bootstrap re-sampling approach for extracting the sub- samples from the primary samples. Next, a decision tree is generated depending on each sample. Second, the categorized decision tree supports a voting mechanism, with the decision tree with the most votes determining the final prediction conclusion. The proposed ensemble algorithm working is described as below;Select the training set: Using the bootstrap random sampling approach, K training sets are retrieved from the original dataset (M properties) in this phase. The training set is taken together with its size, much like the original training set

- Create the RF model by following these steps: A classification regression tree is built for each bootstrap training set, culminating in K decision trees creating a "forest." The trees in the forest have not altered. Because of internal nodes, no tree structure resembles the best qualities. In this situation, branching is accomplished by randomly picking M of all characteristics.
- Implement simple voting: The decision tree training approach is self-contained. Random forest training helps to improve its effectiveness The Ensemble classifier is built using the same combination of trained K decision trees. Once the input samples have been categorized, the simple voting mechanism of each decision tree is used to

select the output. Each decision tree's distributed decisiontrees, independent sample determination, and finalclassification are determined usingthe ensemble algorithm.

- During the process, the noises are removed from the images, and features such as instances, attributes, and the sum of weights are extracted. Then ensemble classifier is used for classification, which results in the resultantclassification tree. Next voting system is applied to the tree node with maximum votes finalized forthe result.

5.2 Convolutional Neural Network Based on Sea Lion Optimization Algorithm for the Detection and Classification of Diabetic Retinopathy

Manual diagnosing of DR retina fundus image is a time consuming process and sometimes leads to misdiagnosis. As a result, the DR is diagnosed in this paper through four critical phases. The retinal images are cropped during preprocessing to reduce unwanted noises and redundant data. The images are then segmented using a modified level set algorithm based on pixel characteristics. Here, an Aquila optimizer is employed in extracting the segmented image. Finally, for optimal classification of DR images, the study proposes a CNN oriented sea lion optimization (CNN-SLO) algorithm. Here, the CNN-SLO algorithm classifies the retinal images into four classes (healthy, moderate, mild, proliferative and severe). Figure 5.1 depicts the augmented basic workflow of the proposed methodology consisting four vital phases namely the data pre-processing, segmentation, feature extraction as well as classification phases for optimal DR disease detection and classification. The steps concerned in DR disease detection are described in a below subsections.

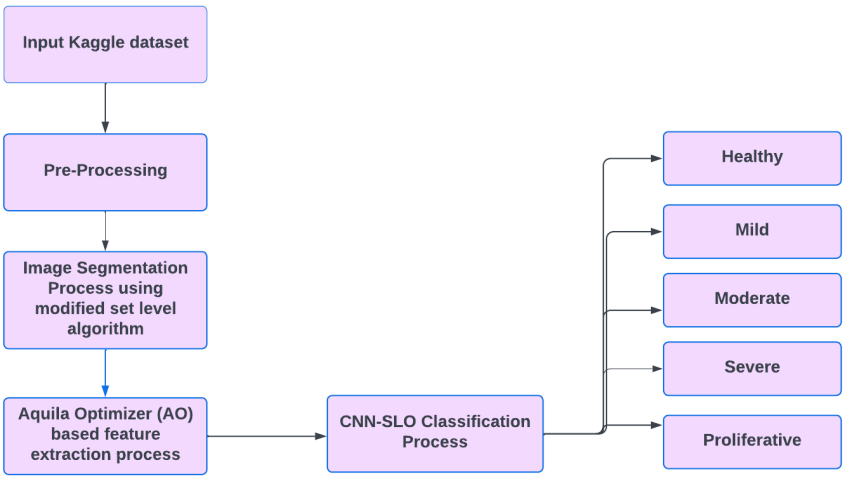

Figure 5.1 Proposed approach with its workflow model

5.2.1 Data pre-processing phase

The fundus images are taken in diverse environmental circumstances. Because of the presence of impulse noise in the image under these conditions, the captured new image might lose its primary information. For minimizing the data alterations, the image pre-processing stage is considered as an important stage that assists to employ the performance of classification thereby emphasizing the tiny image details. As well as, the quality and intensity of the image is increased during pre-processing. This minimizes the trouble during segmentation, extraction as well as classification.

5.2.2 Segmentation based on modified level set algorithm

This is the technique in which the obtained pre-processing images are broken down into diverse subgroups referred to as image segments. After the preprocessing method, the images be divided into various sections based on the characteristics of images. A preprocessed image is the input of the segmentation stage. Hence the images are separated into two such as blood vessels and optic disks. The segmentation process assists in minimizing the image complexity that makes analyzing or processing the image simpler. This work employs modified level set algorithm in segmenting the images based on image pixel characteristics. The modified level set algorithm is considered as an excellent technique in segmenting the images due to its high edge strength, speed function as well as region intensity. The following section depicts the mathematical expressions to generate modified level algorithm.

Initially, the entropy of an image is intended for calculating the totality value of information and is expressed mathematically as;

$$e = -\sum_{m} Q_m \left[Log_2 Q_m \right] \tag{5.1}$$

From equation (5.1), the probability difference within the nearby pixels is represented by Q_m. The Gaussian filter utilize the persona malik diffusion (PMD) filter for image smoothening and is represented by;

$$\begin{aligned} \frac{\partial N}{\partial A} &= D\left[d(l,o,u) \nabla K \right] \\ &= \nabla d . \nabla N + d(l,o,y) \nabla K \end{aligned} \tag{5.2}$$

From the above equation, the laplacian factor is denoted by Δ in which a gradient is ∇, the divergence operator is expressed by $D(...)$ and $d(l,o,u)$ represent diffusion coefficient that

manages the value of diffusion to keep the edges of an images. The magnitude of the gradient image after smoothing is conveyed as;

$$G_{MAG} = \frac{|\nabla C(l,o)| - MIN[|\nabla C(l,o)|]}{MAX[|\nabla C(l,o)|] - MIN[|\nabla C(l,o)|]} \quad 5.3$$

To control the movement of the gradient image, the modified speed function is computed on the basis of the negative exponential product, and the contour is expressed by,

$$\hat{L_K} = Exponential[-KL_K^2] \quad 5.4$$

The contour control motion is k represented by in equation (5.4), and the current contour is evaluated. Therefore, the retinal images are effectively segmented by using the modified level set algorithm.

5.2.3 CNN-SLO based classification process

Subsequent to the extraction process, the classifications of DR images are carried out. The classification phase plays a vital role in classifying the DR images into five types of severity levels namely the healthy, mild, moderate, severe and proliferative. This paper proposes a novel a CNN based sea lion optimization (CNN-SLO) algorithm for effective classification of DR disease based on severity classes. Generally, CNN is one of the Deep Learning techniques which take the input images, allocate biases and weights to different objects/aspects within the images, and can be capable to distinguish each other in order. The advantage of utilizing CNN is the capability to evolve an internal expression for two-dimensional images.

A Convolutional layer is one of the primary building blocks and it includes a group of kernels, a parameter that is learned across the training. The size of kernels is generally lesser than the real image. Each kernel generates the activation maps and convolutes the image. The down-sample working function is achieved through the pooling layer. The pooling layer's function is to gradually reduce the dimensional size of the representation in order to reduce the amount of computation and parameters in the networks. *Fully connected (FC) layer* is known as the hidden layer that is similar to artificial neural networks (ANN). The input of the FC layer gives the outcome from the Convolutional or final pooling layer, which is fed within the FC layer and leveled. The softmax layer estimates the stochastic distribution of the specific event through various events. This function calculates every object's probabilities $P(A_L^M)$ through all

probable objective groups. The softmax layer is determined by the mathematical expression is calculated by;

$$P(A_L^M) = \frac{Ex(A_L^M)}{\sum_{L=1}^{J} Ex(A_L^M)} \quad 5.5$$

The CNN weights are optimized with the usage of sea lion optimizer. This optimization technique is utilized due to high convergence speed and easy computation.

5.2.3.1 Sea Lion optimization (SLO)

Sea lions are one of the most brilliant animals in the world and it is very large. Sea lions are aquatic mammals named pinnipeds that vary in physical adaptations and features. They are brown in color and they use large flippers to walk and they have clear ear flaps. It is usually not dangerous for humans and attacks are unusual but they are having sharp teeth, a big chest, and a big belly. The main predators of sea lions are sharks, whales, and humans. Sea lions are harvesting for blubber, oil, and meat. Their bones and whiskers are utilized for tools, stomachs and intestines are used for clothing, and waterproof containers, skins are utilized for kayaks. The mathematical expression for the SLO method is followed as;

Track and detect stage

Sea lion can determine the place of prey and call other sea lions, hence they will join and form a subgroup to hunt and find the prey. The Sea lion is the leader for the chasing mechanism and other sea lions upgrade their places to target prey. To determine track and detect stage is expressed as;

$$\overline{D} = \left| \overline{2A} . \overline{Q(u)} - \overline{TM(u)} \right| \quad 5.6$$

The distance between the sea lion and the target prey is represented by $\overline{D}$; the position vectors of the sea lion and target prey is denoted by $\overline{Q(u)}$ and $\overline{TM(u)}$ respectively. u represents the current iteration and $\overline{A}$ is represented by a random vector.

$$\overline{TM(u+1)} = \overline{Q(u)} - \overline{D}.\overline{E} \quad 5.7$$

The next iteration is represented by $(u+1)$ and $\overline{E}$ is decreasing from 2 to 0 in the course of iterations.

Sea lions are known as amphibians they live in both water and land. The movement of sea lions sounds is four times faster compared with air. They employ different vocalizations for conveying their expressions with each other, particularly for tracking and detecting and they form a subgroup. Sea lions have tiny ears that are used for the detection of sounds under and above water. Sea lions are capable to attack the position of pointed prey and surround them. This hunting process is directed by the head to find the prey and they says the other sea lions about it.

5.3 Hybrid Adaptive Deep Learning Classifier for Early Detection of Diabetic Retinopathy Using Optimal Feature Extraction and Classification

In this work, we proposed a Hybrid Adaptive Deep Learning classifier for early detection of Diabetic Retinopathy (HADL-DR). First, we provide an improved Multichannel-based Generative Adversarial Network (MGAN) with semi-maintenance to detect blood vessels segmentation. By reducing the reliance on the encoded data, the following high-resolution images can be used to detect the indivisible features of some semi-observed MGAN references. The SIFT function is then extracted and the best function is selected using the improved Sequential Approximation Optimization (SAO) algorithm. After that, a hybrid Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) is utilized for DR classification.

5.3.1 System design of proposed HADL-DR technique

Figure 5.2 shows the system architecture of proposed HADL-DR technique in which the retinal fundus image as input to classify DR. The input image is preprocessed to improve the image data that surpasses the unwanted noise and distortions. The image conversion techniques also eliminate the unwanted data from the original image. We use semi supervision MGAN algorithm for blood vessel segmentation which segment blood vessels area from original image. Then, we use SAO algorithm for multi-feature extraction from segmented blood vessels which enhance the prediction accuracy. At last, a new RNN-LSTM classifier is send for DR disease classification for human-beings with single retinal fundus image.

In this proposed work, we first discuss the working process of blood vessel segmentation. After that, we discuss the process of feature extraction and optimal feature selection. Finally, we discuss the process of DR detection and classification using hybrid classifier.

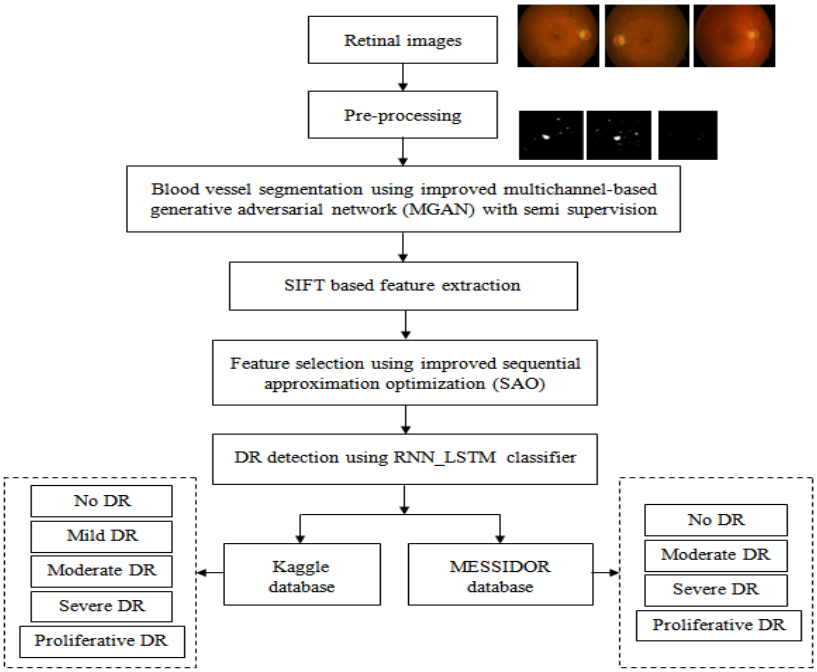

Figure 5.2 System design of proposed HADL-DR technique

5.3.2 Blood vessel segmentation using semi supervision-MGAN

In this section, the vascular symbol MGN, which uses a high-resolution fundy image without the MGN abbreviation, was created by multimedia-based Reproduction Consultation Network (MGAN) plate segmentation and associated with a scattered DR component in an intermediate pattern. An array of di-images was created in the hip band above. We insist that the complex languages we deal with should not be used. Therefore, the final publication was automatic for each generation. The mathematical model of the MGAN with semi supervision is signified by considering the population of universes u as:

$$u = \begin{bmatrix} X_1^1 & X_1^2 & \cdots & X_1^p \\ X_2^1 & X_2^2 & \cdots & X_2^p \\ \vdots & \vdots & \vdots & \vdots \\ X_N^1 & X_N^2 & \cdots & X_N^p \end{bmatrix} \tag{5.8}$$

$$X_r^q = \begin{cases} X_z^q & if \;\; i_1 < nR(u_r) \\ X_r^q & otherwise \end{cases} \tag{5.9}$$

where $i_1 \in [0,1]$; 1 is a random number, u_r is the r^{th} universe, and $nR(u_r)$ is normalized inflation rate (fitness value) of the u_r. Less inflation rate indicates high export potential in white/black hole tunnels. Each u_r contains wormholes (which carry objects in space), protecting it with the diversity of the universe. These wormholes transform objects in the anti-inflation world into

random shapes. In addition, holes are being used to improve the global situation and raise inflation, which is the best way to change the global exchange rate.

$$X_r^q = \begin{cases} \begin{cases} X_q^m + TDR \times \left(\left(UB_q - LB_q \right) \times i_4 + LB_q \right) i_3 < 0.5 \\ X_q^m - TDR \times \left(\left(UB_q - LB_q \right) \times i_4 + LB_q \right) i_3 \geq 0.5 \end{cases} & i_2 < WEP \\ X_r^q & i_2 \geq WEP \end{cases} \quad 5.10$$

where X_q^m shows the q^{th} parameter in the best solution.

$$TDR = 1 - \frac{y^{1/d}}{Y^{1/d}} \quad 5.11$$

If y is equal to the current frequency, y represents the length of the frequency and d is the default value of 6, which defines the accuracy of the frequency application. Wormhole existence probability (WEP) is used to linearly increase frequency to emphasize abuse, and WEP is defined as follows:

$$WEP = WEP_{MIN} + y \times \left(\frac{WEP_{MAX} - WEP_{MIN}}{Y} \right) \quad 5.12$$

where WEP_{MIN} 0.2 equals as default value, WEP_{MAX} equals 1 as a default value. The following equation shows the overall computational complexity:

$$Q(mvo) = Q\left(L\left(N^2 + N \times p \times \log N \right) \right) \quad 5.13$$

where inventory is the number of units that currently contained in the process and flow time is the time spent in the process from the beginning to end. From the collected information, we compute blood vessel segment as follows:

$$F_p = \left(e_{TOTALp} + cr_p + Dlr_p + Tp_p \right) \quad 5.14$$

5.3.3 Feature extraction and optimal feature selection

After blood vessel segmentation, the SIFT feature are extracted and optimal feature selection is done by improved sequential approximation optimization (SAO) algorithm.

The scale-invariant feature transform (SIFT) function is based on the shape of the object at specific locations and locations of interest, as well as the size and rotation of the image. It is also powerful against small changes in light, sound and vision. In addition to these properties, they are very unique, relatively easy to distinguish, and identify the exact object with the lowest probability of non-compliance. At the base of the retina, we need some selection algorithms

for image analysis capabilities. These properties are calculated from SIFT's main properties such as mean, constant variation, contact, smoothness, third order, uniformity, curvature, and entropy. Here, average means the average intensity of a separated retinal image with different intensities in different parts of the image.Mean (M), is a measure of average intensity:

$$M = \sum_{n=0}^{l-1} (a_n u \times (a_n)) \tag{5.15}$$

where, a_n denotes the size of the image, u is the size of the segmented image. The standard deviation is the square root of the variance. Here, it is used to measure how spread out the random variable of the segmented image is, on average, from the mean. Standard deviation (α) is a measure of average contrast with $\phi_2(a)$is variance:

$$\alpha = \sqrt{\phi_2(a)} = \sqrt{\alpha^2} \tag{5.16}$$

Here, smoothness refers to the vagueness in the segmented disease area and it gives the intensity of region. Smoothness (s) is a measure the relative smoothness of the intensity in a region:

$$s = 1 - \frac{1}{(1+\alpha^2)} \tag{5.17}$$

where α^2 is the standard deviation. Here, third moment is the rate of asymmetry of a histogram which identifies the uniqueness in the segmented image and helps us find the disease area. Third moment β_3 is a measure of the $(a_n - x)^3 u(a_n)$histogram Skewness:

$$\beta_3 = \sum_{n=0}^{l-1} (a_n - x)^3 u(a_n) \tag{5.18}$$

Here, uniformity denotes the consistency of the data where the frequency of various region of the segmented image is analyzed. Uniformity (W) is a measure the uniformity of intensity in the histogram:

$$W = \sum_{n=0}^{l-1} u^2(a_n) \tag{5.19}$$

where, u is the frequency of each region. Here, entropy is the corresponding states of intensity level which individual pixels can adapt on the segmented image. Entropy (E) is a measure of randomness:

$$E = \sum_{n=0}^{l-1} u(a_n) \log_2 u(a_n) \tag{5.20}$$

5.3.4 Optimal feature selection using improved sequential approximation optimization

In recent years, double optimization methods based on the sequential approximation optimization (SAO) method have been increasingly used to solve landscape optimization problems. Key steps in the SAO system are eliminating additional problems, solving double problems, solving double add-ons that optimization could not control, and updating the final solution. The proposed sequential approximation optimization (SAO) algorithm is derived from the basic sequence approximation. This is especially true for configuration optimization problems that exceed the number of design variable controllers. The main goals are to determine the quality of the process, the approximate control, and the accuracy and efficiency of the project. Approximation calculations are usually done using logistically chaotic map with various intermediate variables.

The working structure of proposed improved SAO algorithm based optimal feature selection is given in Algorithm 2.

5.3.5 DR detection and classification

After optimal feature selection, a hybrid recurrent neural network with long short-term memory (RNN-LSTM) is used to detect and classify DR images. RNN is one of the smartest data mining technologies that identifies and generalizes key data trends. RNN can imitate and analyze complex patterns in structured data compared to traditional methods. So here were fuse RNN with the LSTM to make hybrid multi-objective deep learning technique. Here, each layer size i of CN_j was activated as follows:

$$CN_{ji} = CN_{Minj} + Rand[0,1](CN_{Maxj} - CN_{Minj}) \tag{5.21}$$

where CN_{Maxj} and CN_{Minj} are limits of CN_j in ith position [0, 1] and direction and random is a random number that is evenly distributed over the range [0, 1].Level upgrade equation for CN

$$\begin{aligned} CN_{Newji} = CN_{ji} + Rand[0,1](WW_{zi} - CN_{ji}) + \\ Rand[-1,1](CN_{si} - CN_{ji}) \end{aligned} \tag{5.22}$$

where the jth dimension of the ith CN is denoted by CN_{ji}, the ith scale of the local group leader position indicates zth WW_{zi}. The level update equation for the global leader level is given

$$CN_{Newji} = CN_{ji} + Rand[0,1](FW_{zi} - CN_{ji}) + Rand[-1,1](CN_{si} - CN_{ji}) \quad 5.23$$

where FW_{zi} is the ith the dimension of the global leader position and i [{1, 2, …, D} is an randomly selected list. The probability $PROB_j$ is calculated as follows

$$PROB_j = 0.9 \times \frac{Fitness_j}{Max\ fitness} + 0.1 \quad 5.24$$

This is done using the level upgrade equation at the local leader stage

$$CN_{Newji} = CN_{ji} + Rand[0,1](WW_{zi} - CN_{ji}) + Rand[-1,1](CN_{si} - CN_{ji}) + g(CN_{si} - CN_{ji}) \quad 5.25$$

where g is determined by GSS process. This is done using the level update equation, in the global leader phase

$$CN_{Newji} = CN_{ji} + Rand[0,1](FW_{zi} - CN_{ji}) + Rand[-1,1](CN_{si} - CN_{ji}) + g(CN_{si} - CN_{ji}) \quad 5.26$$

G is defined by the GSS process. The modified equations are:

$$CN_{Newji} = CN_{ji} + PROB_j(WW_i - CN_{ji}) + (1 - PROB_j)(CN_{si} - CN_{ji}) \quad 5.27$$

$$CN_{Newji} = CN_{ji} + PROB_j(FW_i - CN_{ji}) + (1 - PROB_j)(CN_{si} - CN_{ji}) \quad 5.28$$

$$CN_{Newji} = CN_{ji} + PROB_j(FW_i - CN_{ji}) + (1 - PROB_j)(CN_{ji} - WW_{zi}) \quad 5.29$$

where $PROB_j$ the probability which depends on fitness. Capuchin fitness is used to calculate size according to the status update process. Status is updated in the Global Leader phase using the following equation:

$$CN_{Newji} = CN_{ji} + Rand[0,2.2 - PROB_j](FW_i - CN_{ji}) + Rand[-(2.2 - PROB_j),2.2 - PROB_j](CN_{si} - CN_{ji}) \quad 5.30$$

Three distinct solutions $B(b_1, b_1, ..., b_D)$, $A(a_1, a_1, ..., a_D)$ and $H(h_1, h_1, ..., h_D)$ are B,A and H were randomly selected as the most suitable solution. The minimum point of a square curve that passes through B, A, and H provides a new solution $Q(q_1, q_1, ..., q_D)$ J is the value used in the following equation and g(B), g(A)and g(H) are The value of the objective function of g in B, A, and H respectively.

$$q_j = \frac{1}{2}\frac{(a_i^2 - h_i^2)g(B) + (h_i^2 - b_i^2)g(A) + (b_i^2 - a_i^2)g(H)}{(a_i - h_i)g(B) + (h_i - b_i)g(A) + (b_i - a_i)g(H)} \quad 5.31$$

The current situation written as follows

$$H_{(T)} = g(H_{(T-1)}, Y_T) \quad 5.32$$

Here, H_T is the new state, $H_{(T-1)}$ is the previous state while Y_T is the current input. The activation function is $\tan H$, load on a continuous neuron is L_{HH} and the load at the input neuron is L_{YH}, Let's write the equation for the state when necessary T as

$$H_T = \tan H(L_{HH}H_{T-1} + L_{YH}Y_T) \quad 5.33$$

The output layer can be calculated as follows

$$X_T = L_{HX}H_T \quad 5.34$$

Now we can get to the hidden layer,

$$H_T = \tan H(L_{HH}H_{T-1} + L_{XH}Y_T) \quad 5.35$$

There is no previously hidden layer for H, we apply the $\tan H$ function on this release and get the current status.

6. THESIS ORGANIZATION

The thesis of this research work is organized into six chapters as stated below.

Chapter 1- 'Introduction' details about the introduction of DR and its stages using retinal images. The various parts of retina are elaborated and different eye related diseases are discussed in this chapter. The objectives, motivation, contributions of this research work are stated in this chapter.

Chapter 2- 'Literature Survey' states and discusses various existing methodologies of DR using retinal images. This chapter also states the main findings and limitations of each existing study with their experimental results.

Chapter 3- 'Diabetic Retinopathy Prediction and Analysis Using Ensemble Classifier in Deep Learning Technique' propose an Ensemble algorithm to predict diabetes from retinal images. The primary goal of this work is to enhance the accuracy and predict the result with minimum time consumption. The proposed system is a two-phase work in which, the initial bootstrap re-

sampling method is employed for extracting the subsamples. Next, the classified decision tree establishes a voting system for finalizing the prediction result. The performance accuracy achieved by the proposed Ensemble algorithm is compared with the logistic regression and Deep Neural Network (DNB).

Chapter 4- 'Convolutional Neural Network based SEA Lion Optimization ALGORITHM for the detection and classification of diabetic retinopathy' presented CNN-SLO algorithm for better classification of DR images. This study employed four vital phases namely the data pre-processing phase, image segmentation, feature extraction as well as classification phase. **A modified level set algorithm** as well as **Aquila optimizer** is introduced in segmenting and extracting the DR images respectively. The **CNN-SLO algorithm** classifies the retinal images into four classes (healthy, mild, moderate, severe and proliferative).

Chapter 5- 'Hybrid adaptive deep learning classifier for early detection of diabetic retinopathy using optimal feature extraction and classification' proposed a hybrid adaptive deep learning classifier for early detection of diabetic retinopathy (HADL-DR). An improved **multichannel-based generative adversarial network (MGAN) with semi supervision** technique is proposed for detect the blood vessel segmentation. **The SIFT featur**es are extracted and the **improved sequential approximation optimization (SAO)** algorithm used for optimal feature selection. A hybrid recurrent neural network with long short-term memory **(RNN-LSTM)** is used to make the classification of DR images as multiple disease class.

Chapter 6- 'Conclusions and Future works' discusses the main findings of each proposed methods for DR detection and classifications. This chapter also discusses the main advantages of each proposed work and also states the future implementation of this research work in detail.

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8. LIST OF PUBLICATIONS

- **S.V.Hemanth,** and **A.Sarvanan**., Diabetic Retinopathy Prediction and Analysis Using Ensemble Classifier in Deep Learning Technique**, (OTCON),** (2023).[**IEEE-Conference**] **[Published].**

- **S.V.Hemanth,** and **A.Sarvanan**., Hybrid adaptive deep learning classifier for early detection of diabetic retinopathy using optimal feature extraction and classification., Journal of Diabetes and Metabolic Disorders, ,(2023).**[ESCI-SCOPUS] [Published]**

- **S.V.Hemanth, A.Sarvanan** and **T Dhiliphan Rajkumar.**, Convolutional Neural Network Based Sea Lion Optimization Algorithm for the Detection and Classification of Diabetic Retinopathy.,Acta Diabetologica, (2023). **(SCI-IF: 4.087) [Accepted].**